Electronic Journal of Applied Statistical Analysis
EJASA, Electron. J. App. Stat. Anal.
http://siba-ese.unisalento.it/index.php/ejasa/index
e-ISSN: 2070-5948
DOI: 10.1285/i20705948v9n3p736

Technical efficiency with several stochastic frontier analysis models using panel data

By Crisci, Siviero, D'Ambra

Published: 15 December 2016

Electronic Journal of Applied Statistical Analysis
Vol. 09, Issue 04, December 2016, 736-759
DOI: 10.1285/i20705948v9n3p736

Technical efficiency with several stochastic frontier analysis models using panel data

Anna Crisci*[a], Lucio Siviero[b], and Luigi D'Ambra[c]

[a]*Pegaso Telematic University, Department of Law and Economic Sciences, Piazza Trieste e Trento, Napoli (Italy)*
[b]*University of Study of Catania, Department of Economics and Business, Corso Italia, Catania (Italy)*
[c]*University of Naples, Federico II, Department of Economics, Management and Institutions, via Cinthia, Napoli (Italy)*

Published: 15 December 2016

The paper discusses technical efficiency analysis of Italian rail terminals for a panel data from 2007 to 2011 considering variables related to production factors with a dynamic vision over time. The use of panel data makes the researchers investigate whether inefficiency represented by the one-sided part of the error term varies or is constant over time. This paper uses techniques, time varying and time invariant, relating to the estimation of stochastic production functions and of technical efficiency in order to analyze the production performance of rail-road modal interchange terminals in Italy.

keywords: Panel Efficiency Model, Stochastic Frontier Analysis, Time Varying Model, Time Invariant Model, Rail-Road Terminal

1 Introduction

Stochastic Frontier Model (SFA) was first proposed by Meeusen and van den Broeck (MB) (Meeusen and Van den Broeck, 1977) and Aigner, Lovell, and Schmidt (ALS) (Aigner et al., 1977), who started the tradition of specifying a one-sided error distribution for the inefficiency. Later, the researches of SFA were developed by Greene (Greene, 1980a, Greene, 1980b), who developed the distribution-related ideas, by Stevenson (1980)

*Corresponding author: anna.crisci@unipegaso.it

ISSN: 2070-5948
http://siba-ese.unisalento.it/index.php/ejasa/index

who let the mode of inefficiency to be positive, and by Jondrow, Lovell, Materove and Schmidt (Jondrow et al., 1982), who discovered an estimator for the level of inefficiency. But all these researches were based on cross-sectional datasets, which had some original shortcomings. For this reasons, the panel data was introduced into stochastic frontier analysis context. Pitt and Lee (1981) and Schmidt and Sickles (1984) discuss the disadvantages of estimating the production frontier by other data and highlight the advantages of using panel data to estimate production frontier, such as fever assumptions required and consistent technical inefficiency estimates. The use of panel data makes the researchers investigate whether inefficiency represented by the one-sided part of the error term varies over time or is constant over time. In this paper we consider the SFA with longitudinal data. The first studies on longitudinal data for stochastic frontier approaches go back to the work done by Pitt and Lee (1981) and Schmidt and Sickles (1984). In particular, the authors assumed that technical inefficiency is time-invariant, while Cornwell, Schmidt, and Sickles (Cornwell et al., 1990), Kumbhakar (1990), and Lee and Schmidt (1993) stated the strong time-invariant assumption, which allowed the technical inefficiency to be time varying. Later, Lee and Schmidt (1993) and Battese and Coelli (1995) also introduced other models to estimate the time varying panel data stochastic frontier and technical inefficiency. Greene (Greene, 2005b, Greene, 2005a), underlined the shortcomings of traditional panel data models when dealing with time-invariant heterogeneity, and suggested the true fixed-effects model and true random effects model.

This paper uses techniques, time varying and time invariant, relating to the estimation of stochastic production functions and of technical efficiency in order to analyze the production performance of rail-road modal interchange terminals in Italy over the period 2007-2011.

It is organized as follows: in section 2 the econometric models are explained: Time Invariant, Time Varying and Pooled. In Section 3 the data and variable constructions are shown. In Section 4 and in section 5, a comparison among several econometric models with main results and final discussion are shown.

2 The econometric models: Time Invariant, Time varying and Pooled

The estimation of stochastic production frontiers for cross-sectional data was simultaneously proposed by Aigner, Lovell and Schmidt (Aigner et al., 1977) and Meeusen and Van den Broeck (1977). Pitt and Lee (1981) and Schmidt and Sickles (1984) deduce the disadvantages of estimating the production frontier by cross-section data and highlight the advantages of using panel data to estimate production frontier. Panel data have several advantages over pooled data (Baltagi, 1985):

- Accounting for heterogeneity across individuals units which is assumed away in pooled data;
- Dealing with time-invariant omitted variables as we can find in pooled data;

- Appropriate modifications in the model specification and the method of estimation are available to take care of problem with autocorrelation and multicollinearity like time series data do.

Panel data sets are also better able to identify and estimate effects that are simply not detectable in pure cross-section or pure time series data.

The goal of this paper is not to investigate all existing panel data models, as it is already known, that different models give different results. So we have selected some pooled and panel data models (time invariant and time varying), and investigated the results from these when applied to the same data set. The main models are briefly specified in Table 1.

Table 1: Models specification

Panel Time Invariant Model	Panel Time Varying Model	Pooled Model
Pitt and Lee (1981)	Battese and Coelli (1991)	Aigner et al. (1977)
Battese and Coelli (1988)	Battese and Coelli (1995)	Stevenson (1980)
	Greene (2005a) (TFE, TRE)	

To analyze these models, we gave them the same expression, but different models are specified for different parameter assumptions.

The function is given as:

$$y_{it} = \alpha + f(\mathbf{x}_{it}^{'}\mathbf{b}) + \epsilon_{it} \tag{1}$$

where y_{it} is the log of output for rail-road terminal i at the time t; f is a function that indicates or Cobb Douglas or translog, etc.; $i = 1, 2, ..., N$; $\mathbf{x}_{it}$ is a (k x 1) vector of input quantities for rail-road terminal i at the time t; $\mathbf{b}$ is an vector of unknown parameters; $\epsilon_{it} = v_{it} - u_{it}$, where v_{it} are random variables which are assumed to be iid $N\ (0, \sigma_v^2)$, and independent of the u_{it} which are non-negative random variables which are assumed to account for technical inefficiency in production.

2.1 Time invariant and time varying econometric models

According to the relationship between technical inefficiency and time, panel data is separated into two types: one is the time-invariant model, which assumes that technical inefficiency is constant over time, without any technical change over time, labeled as u_i; the other one is the time-varying model, which allows technical inefficiency to change over time, labeled as u_{it}. Under a panel data generating process, the inefficiency component is assumed to be correlated over time; when this is applied to the inefficiency component, it results in one of two general forms:

1. $u_{i1} = u_{i2} =...= u_{iT} = u_i$ Time invariant
2. $u_{i1}= u_i g(1)$,..., $u_{iT} = u_i g(T)$ i.e. $u_{it} = u_i g(t)$ Time varying

2.2 Time invariant models

2.2.1 Pitt and Lee (1981) and Battese and Coelli (1988)

Pitt and Lee (1981) and Schmidt and Sickles (1984) were the first to consider stochastic frontier models with panel data. They considered the model with time invariant inefficiencies:

$$y_{it} = \alpha + f(\mathbf{x}_{it}^{'}\mathbf{b}) + \ v_{it} - u_i \qquad i = 1, 2, ..., N, t = 1, 2, ..., T \tag{2}$$

where $u_i \sim iid\ N^{+}(0,\sigma_u^2)$

This equation can be converted to standard panel data model:

$$y_{it} = \alpha_i + f(\mathbf{x}_{it}^{'}\mathbf{b}) + \ v_{it} \qquad i = 1, 2, ..., N, t = 1, 2, ..., T \tag{3}$$

If the u_i are fixed parameters (as in Schmidt and Sickles, 1984), then the u_i term can be combined with the common intercept, i.e., $\alpha_i = \alpha + u_i$ so that all the α_i parameters can be identified, for example, from the coefficients of the rail terminals dummies. Inefficiency u_i can be estimated from $\hat{u_i} = max_i(\hat{\alpha}_i) - \hat{\alpha}_i \geq 0$ where $\hat{\alpha}_i$ is the fixed terminal effect in the standard panel data model. This makes the best terminal (highest intercept) fully efficient and thus inefficiency for other terminal is relative to the best rail terminal. The advantage of this approach is that it is not necessary to make any distributional assumptions about inefficiency term. The disadvantage is that we cannot use any time-invariant covariates to explain inefficiency. If u_i is assumed to be a half truncated normal random variable (Pitt and Lee, 1981; Kumbhakar, 1990; Battese and Coelli, 1988), the parameters of the model can be estimated by Maximum Likelihood (ML) method. In Pitt and Lee (1981): $u_i \sim iid\ N^{+}(0,\sigma_u^2)$.

Battese and Coelli (1988) considered the more general truncated normal distribution with $u_i \sim iid\ N^{+}(\mu,\sigma_u^2)$. These authors derived their results for the case of balanced panels, while Battese, Coelli and Colby (Battese et al., 1989) generalized the model for the case of an unbalanced dataset. The assumption of time-invariant inefficiency is somewhat more plausible in very short panels, but it is highly unlikely when the number of years/periods is large. It is reasonable to assume that technical efficiency follows some form of pattern over time. Whether this pattern is common among all rail terminals is also an important assumption to consider. It is possible (or one would like to believe) that inefficient rail terminals become more efficient over time. Likewise, it is also possible that some rail terminals become less efficient before leaving the sample entirely (shutting down) in long unbalanced panels. The choice of temporal assumptions depends upon the length of the panel and the nature of the sample. Furthermore, the longer the panel, the less likely it is that technology remains constant. Technical progression (or regression) can easily be incorporated by adding a time trend or annual time dummies to the specification.

2.3 Time Varying Model

2.3.1 Battese and Coelli (1991)

Battese and Coelli (Battese et al., 1989) proposed a stochastic frontier production function for (unbalanced) panel data which has rail terminal effects which are assumed to be distributed as truncated normal random variables, and are able to vary systematically over time. The model may be expressed as:

$$y_{it} = \alpha_t + f(\mathbf{x}_{it}^{'}\mathbf{b}) + v_{it} - u_{it} = \alpha_{it} + f(\mathbf{x}_{it}^{'}\mathbf{b}) + v_{it} \qquad i = 1, 2, ..., N, t = 1, 2, ..., T \tag{4}$$

where $\alpha_{it} = \alpha_t - u_{it}$ is the intercept for rail terminal i in period t; $u_{it} \sim iid\ N^{+}(\mu, \sigma_u^2)$.

Note that we admit a time varying common intercept α_t. Obviously, in order to estimate u_{it} (or α_{it}) we have made some assumptions about their temporal pattern. Therefore, different models proposed depend on the form of α_{it} (or, equivalently, u_{it}).

Specifically, in Battese and Coelli (1991) the u_{it} are assumed to have exponential function of time, involving only one parameter, such as:

$$u_{it} = \{exp[-\eta(t - T)]\}\, u_i \tag{5}$$

where u_{it} is assumed to have truncated normal distribution and η is an unknown parameter to be estimated, which determines whether inefficiencies are time varying or not. As $\frac{\partial lnu_{it}}{\partial t} = -\eta$ the technical inefficiency decays, remains constant or increases over time if $\eta > 0$, $\eta = 0$ and $\eta < 0$, respectively. One advantage of this model specification is that the inclusion of a time trend into the production function permits the estimation of both technical change and changes in the technical inefficiencies over time. As many authors note, this exponential function is very strict.

Another model proposed by Kumbhakar (1990) has the following specification:

$$u_{it} = \left\{1 + exp[(bt + ct^2)]\right\}^{-1} u_i \tag{6}$$

The Kumbhakar function lies in the unit interval and can be non-increasing, non-decreasing, concave or convex depending on the signs and magnitudes of b and c.

Finally, Lee and Schmidt (1993) proposed an alternative formulation:

$$u_{it} = d_t u_i \tag{7}$$

where d_t is specified as a set of time dummy variables. This model is appropriate for short panels, since it requires estimation of *T-1* additional parameters. The model estimates both fixed and random-effects versions of the model (7). In the fixed effects case both d_t and u_i are considered as fixed terms and in the random effects case u_i is treated as a random variable. Lee and Schmidt (1993) used a least squares estimator, while a generalized method of moments approach to the estimation of the model has been developed by Ahn, Lee and Schmidt (Ahn et al., 2001). The parameters of the stochastic frontier and the model for the technical inefficiency effects are estimated simultaneously by maximum likelihood.

2.3.2 Battese and Coelli (1995)

A number of empirical studies have estimated stochastic frontiers and predicted efficiency levels regressing the predicted efficiencies upon specific variables (Pitt and Lee, 1981). The two-stage estimation procedure has also long been recognized as one which is inconsistent in its assumptions regarding the independence of the inefficiency effects in the two estimation stages. The two-stage estimation procedure is unlikely to provide estimates which are as efficient as those that could be obtained using a single-stage estimation procedure. This issue was discussed by Kumbhakar, Ghosh and McGukin (Kumbhakar et al., 1991) and Reifschneider and Stevenson (1991) who proposed stochastic frontier models in which the inefficiency effects u_i are expressed as an explicit function of a vector of specific variables and a random error. Battese and Coelli (1995) proposed a model which is equivalent to the (4) where u_{it} are non-negative random variables which are assumed to account for technical inefficiency in production and are assumed to be independently distributed as truncations at zero of the $N^+(\mu_{it}, \sigma_u^2)$ distribution; where:

$$u_{it} = \mathbf{z}_{it}\delta \tag{8}$$

where $\mathbf{z}_{it}$ is a $p \times 1$ vector of variables (such as covariates or time variables) which may influence the efficiency and δ is an $1 \times p$ vector of parameters to be estimated.

2.3.3 True fixed effect (TFE) and true random effect (TRE) (Greene, 2005a; Greene, 2005b)

True fixed effects model and true random effects were first proposed by William Greene (Greene, 2005b; Greene, 2005a). The main argument is that the inefficiency component in the traditional fixed effects model or random effects model absorbs the cross unit heterogeneity which should be presented as regressors in the function but not as inefficiency.

The true fixed effects model can be expressed as:

$$y_{it} = \alpha_i + f(\mathbf{x}_{it}'\mathbf{b}) + \ v_{it} - u_{it} \tag{9}$$

where α_i is the unit specific intercept intended to capture all time invariant heterogeneities; $u_{it} \sim iid\ N^+(0,\sigma_u^2)$.

The random effects model is written as:

$$y_{it} = \alpha_i + f(\mathbf{x}_{it}'\mathbf{b}) + \ v_{it} - u_{it} + \omega_i \tag{10}$$

where ω_i is a time invariant unit specific random term designed to capture cross unit invariant heterogeneity; $u_{it} \sim iid\ N^+(0,\sigma_u^2)$.

2.4 Pooled Models

2.4.1 Aigner, Lovell and Schmidt (1977) and Stevenson (1980)

Another type of data set, which is similar to panel data, is pooled data. Pooled data also includes the observations of rail terminal for several time periods. The main difference between panel data and pooled data is the independence of errors. Both data sets generating processes assume that the error terms are identically distributed: $u_i \sim id\ (\mu, \sigma_u^2)$ in the homoscedastic case. Moreover, under pooled data, an independence hypothesis is inserted: $u_{it} \sim iid\ (\mu, \sigma_u^2)$. This independence assumption does not change over time. This implies that u_{it} and u_{is} (for $t \neq s$) are independently distributed (that is, we have a time varying inefficiency since u_{it} and u_{is} are independent realization of the inefficiency component of the random error).The pooled models considered in this paper are: Aigner, Lovell and Schmidt (ALS) [2] and Stevenson (1980). The sample is considered as a series of cross-sectional sub-samples pooled together and these models can also be estimated as time varying efficiency. These models and assumptions are summarized in Table 2.

Table 2: Econometric specifications of the stochastic production frontier

Econometric Models	Specific component α_i	Inefficiency u_{it}	Random noise v_{it}	Inefficiency estimate
ALS (77) (Pooled)	None	$u_{it} \sim N^+\ (0, \sigma_u^2)$	$v_{it} \sim N\ (0, \sigma_v^2)$	$\mathrm{E}(u_{it} \mid \epsilon_{it})$
Stevenson (80) (Pooled)	None	$u_{it} \sim N^+\ (\mu, \sigma_u^2)$	$v_{it} \sim N\ (\mu, \sigma_v^2)$	$\mathrm{E}(u_{it} \mid \epsilon_{it})$
B&C (92)	None	Truncated normal $u_{it} \sim N^+\ (\mu, \sigma_u^2)$ u_{it}=(exp $[-\eta(t-T)]$) u_i	$v_{it} \sim N\ (0, \sigma_v^2)$	$\mathrm{E}(u_{it} \mid \epsilon_{it})$
B&C (95)	None	Truncated normal $u_{it} \sim N^+\ (\mu_{it}, \sigma_u^2)$ $u_{it}= z_{it}\delta$	$v_{it} \sim N\ (0, \sigma_v^2)$	$\mathrm{E}(u_{it} \mid \epsilon_{it})$
Pitt and Lee (81)	None	Half Normal $u_i \sim N^+\ (0, \sigma_u^2)$	$v_{it} \sim N\ (0, \sigma_v^2)$	$\mathrm{E}(u_i \mid \epsilon_{it})$
B&C (88)	None	Truncated Normal $u_i \sim N^+\ (\mu, \sigma_u^2)$	$v_i \sim N\ (0, \sigma_v^2)$	$\mathrm{E}(u_i \mid \epsilon_{it})$
Greene (05) (TFE)	Fixed	Half Normal $u_{it} \sim N^+\ (0, \sigma_u^2)$	$v_{it} \sim N\ (0, \sigma_v^2)$	$\mathrm{E}(u_{it} \mid \epsilon_{it})$
Greene (05) (TRE)	$\alpha_i \sim N\ (0, \sigma_\alpha^2)$	Half Normal $u_{it} \sim N^+\ (0, \sigma_u^2)$	$v_{it} \sim N\ (0, \sigma_v^2)$	$\mathrm{E}(u_{it} \mid \alpha_{it} + \epsilon_{it})$

3 Data and Variables

In this paper we use a sample of 34 Italian rail-road terminals to assess the developments of technical efficiency in these intermodal terminals over the period 2007-2011. We apply the production frontier models that indicate the maximum production capacity given the combination of available resources.

The most important elements of an intermodal transport network are the terminals, i.e., intermodal nodes, which are infrastructures that connect two or more transport modes. Intermodal terminals may be designed to handle different ITUs (Intermodal Transport Units) and to serve different transportation modes depending on the configuration of the transport network, node locations, accessibility for different transport modes, demand characteristics, transport flow volumes, and so on.

Rail-road intermodal transport is one of the main forms of intermodality and represents an important alternative to mono-modal road transport. Public and private policy choices should be driven by economic reasoning such as the search for optimal use of resources and the subsequent obtainable results. A rail-road intermodal terminal needs to be assessed in the same way as any other production process that requires input in order to obtain output and, in the case in question, the best possible combination of production factors typical of intermodal goods transport services. These factors generally comprise elements linked to specific infrastructures (operational areas, length of rail tracks, moving equipment, etc.) over and above the labour factor (Higgins et al., 2012).

Inefficiency is measured by the extent that a firm deviates from the possible production frontier. Aigner et al. (1977) are among the pioneers proposing the stochastic frontier model (SFM) with maximum likelihood estimators. Since then, the SFM has been applied extensively to industrial analysis particularly for the transport services and terminal infrastructure. The Battese and Coelli (1995) model is one of the guiding examples using SFM in evaluating efficiency of transport infrastructures, specifically container ports (Tongzon and Heng, 2005). An attempt has been made to show more specifically the level of efficiency of Italian rail terminals in relationship to their capacity to attract and handle intermodal rail-road traffic, as a dependent variable, by considering a set of explanatory variables referring to the factors of production used, all expressed in logarithms.

These types of intermodal infrastructures are long term investments designed with a large margin of capacity reservation for the expected growing trading volume (Medda and Liu, 2013). As we assume that the technical efficiency can be estimated by using the ratio between ITU throughput and rail terminal tracks length, the results show the effect of input variables: employment, terminal area surface extension, competition and inclusion in a logistic multi-service environment on the 'rail-road intermodality'efficiency (Boysen et al., 2012).

The sources examined for the construction of the original dataset were: the business websites of the Interports and the Terminali Italia company of Ferrovie dello Stato group, the Unioncamere TRAIL portal, Europlatform freight village portal, UIR Unione Interporti Riuniti website, the Transport and Infrastructure National Account of the Italian Ministry of Infrastructures and Transport. Further dimensional data and traffic statistics for each freight rail terminal were directly obtained from the terminal operators through an original survey[1]. The definition of an output variable descriptive of the production process may prove reductive with respect to the multi-functionality of a structure capable of generating value with heterogeneous and multimodal services.

[1]We would thank Dr Fedele Iannone for collection and construction of survey's dataset

In these terms, the output generated by a rail terminal is described by the variable which expresses the measure of intermodal cargo traffic, Intermodal Transport Units (ITU) throughput. ITUs consist of containers, swap bodies and semitrailers equipped for combined transport, and their movement will take place on fast trunk lines with handling being concentrated in efficient terminals. Terminals must be able to adapt their operations to changing transport requirements (Janic, 2007).

In the parametric SFA and in the technical efficiency applied models, the variable chosen for the definition of the intermodal output is represented by the measure of a rail-road output index (RRI) defined by intermodal rail-road traffic, in the number of ITUs, divided by the length of rail tracks in meters (ln*ITU* minus ln*Rail tracks lenght*). This is an output measure that shows better the technical dimension and the technological configuration in order to describe terminal design, especially in the case of high variability of dimensional features among the infrastructures of the sample. The *Rail tracks length* shows large differences in terminal sizes. In addition, the output variable chosen represents better the utilisation of the availability modal interchange capacity of the terminal, especially in the case of investment strategies oriented to large capacity reservation and consequent overcapacity. Studies relating to Italy have found the under-utilization of rail-road intermodal terminals and relative potential capacity dispersion through indices of tracks and handling and storage areas (Bonara and Focacci, 2002). With reference to the sample data these indicators led to an average level of 32% of the tracks saturation and 19.6% of the area saturation.

Following the parametric approach, in order to determine functional dependence, Pels et al. (2003) carried out an analysis in 34 European airports and evaluated the stochastic frontiers of productivity. In the airport terminals context, in order to evaluate the efficiency on the level of specific operational activities, indicators such as the number of take-off aircrafts per runway, the number of aircrafts per runway length unit, the number of aircrafts per time unit or the number of reloaded cargoes per ramp, are used (Jaržemskiene, 2009).

The total length of tracks (trans-shipment and waiting tracks) affects both terminal dimensions and daily operations. It can be considered as a measure of capacity of the terminal and, consequently also of the capacity limitation that can affect performance and unit costs for ITU transshipped. Ballis and Golias (2002) made a comparative cost analysis for alternative terminal designs (including infrastructure, personnel and train/truck times) and found out the cost versus volume curves covering a traffic volume ranging from 150 to 1200 ITUs/day. Each curve ends when the terminal capacity is exhausted either due to equipment inadequacy (these cases can be easily identified by their characteristic "U"shape) or due to track capacity limitations. In the present study, therefore, the technical efficiency is output oriented considering the productivity of the utilisation of total terminal's tracks due to the lack of detailed data about the composition of loading tracks, waiting tracks and other functions tracks (pick-up and delivery, etc.) available for each Italian terminal.

With reference to input variables, the explanatory variables selected to represent the labour factor and the physical and structural (capital factor) characteristics for the *i-th* terminals are:

- *Employment at the intermodal terminal* (log of units);
- *Intermodal Terminal Area* (log of sq.m.).

Note that we have placed the total length of the rail tracks in the denominator of both y_i and x_i to reduce the size effect as found in literature about railway companies efficiency (Henderson et al., 2005).

With regard to the entrepreneurial environment, the variables selected for the i-th intermodal terminals are:

- *HHI ratio*: log of an index measuring the concentration of the terminals and the competition among firms in the industry and it is considered as one of the efficiency determinants.
- *Interport* (yes/no): a dichotomous variable equal to 1 if the terminal is inside an interport (freight village) and equal to 0 if it is not.

The HHI ratio is invariable among different participants in the same market, but it will vary over time. A relatively high HHI ratio shows a high market power with a low level of competition. We calculate the HHI ratio as the throughput of each terminal out of the total throughputs in the market for each time period. All the models also include a linear time trend variable ($Year$); by capturing neutral technological progress it allows us to distinguish productivity improvements induced by technological change, the movements of the frontier over time, from those deriving from efficiency improvements, which are movements towards the frontier (Yan et al., 2009).

The frontier-shift time effect, represented by the shift of the productive efficiency frontier in a production function, may occur because of significant change such as technological progress. Since transport infrastructure investments are lumpy and, thus, transport infrastructures have little control over adjusting inputs in a short period, terminals should practice a maximization of outputs given input levels. This perspective is a basis of the output-oriented model. This study adopts the output-oriented model as the method of projection to frontiers based on the observation concerning the Italian rail-road freight terminals. In the real world transport infrastructures are closer to being throughput maximizers rather than input minimizers, an example of them being container terminals and ports (Cullinane et al., 2004; Cheon et al., 2010).

4 Estimation of stochastic frontier models

The Maximum-Likelihood Estimation of the parameters in the Cobb Douglas Stochastic Frontier with neutral technological change by including a time trend are illustrated in Table 3 and 4. However, the results of the models TFE and TRE by Greene (2005a), Greene (2005b) for time varying inefficiency are not taken into consideration as the algorithm implemented in the software used to compute the ML estimates failed to converge. We first fit the pooled and panel models to the data set and compare the results of these models on two aspects: the estimation of parameters and the estimation of the inefficiency, λ and γ, where $\lambda = \frac{\sigma_u}{\sigma_v}$ and $\gamma = \frac{\sigma_u^2}{(\sigma_u^2 + \sigma_v^2)}$. In particular, the parameter γ lies in the interval [0,1].

If there is no inefficiency, the value of σ_u would be zero and also, the value of λ would be zero. Here, λ is expected to be significantly different from zero, indicating inefficiency. The null hypothesis γ=0 implies that the technical inefficiency effects are not present in the model. The hypothesis that efficiency is invariant over time (i.e. η=0) has been tested. All these hypotheses have been tested through imposing restrictions on the model and using the generalized likelihood-ratio test statistic (λ^*) to determine the significance of the restriction. The generalized likelihood ratio statistic is defined by:

$$\lambda^* = -2ln\left\{[L(H_0)/L(H_1)]\right\} \tag{11}$$

Where $L(H_0)$ the value of the log likelihood function for the stochastic frontier estimated under the null hypothesis, and $L[(H_1)]$ is the value of the log-likelihood function for stochastic production function under the alternative hypothesis.

The likelihood ratio statistic has an asymptotic distribution equal to a mixture of chi square distributions $(1/2)\chi_0^2$+$(1/2)\chi_1^2$. Kodde and Palm (1986) present critical values for this test statistics .

From Table 3 and 4 we can note that all parameters are significant at the 5% level. Moreover, we have performed several tests by the Likelihood Ratio-Statistics presented in (11). The first null hypothesis, H_0:γ=0, has been rejected, so, it can be concluded that technical inefficiency, associated with the rail terminal, is significant. The second hypothesis tested is H_0:μ=0. In this study this hypothesis is accepted and it indicated that the efficiency is not influenced by time-trend variable. Finally, the hypothesis H_0:η=0, in B&C(92), is accepted, indicating that the efficiency effect is not varying significantly over time. About the technical inefficiency effect model, equation (8) for the B&C(95) model, z_{it} is only composed by the time trend *(Year)* to account for changes in technical (in)efficiency.

Table 3: Stochastic frontier estimation results Pooled and Time-invariant Models

Production Frontier	Stevenson (80) Pooled	Pitt and Lee (81) Time-invariant	B&C (88) Time-invariant
Wald Test	Wald $\chi^2(5)$= 204.88 $Pr. > \chi^2$= 0.000	Wald $\chi^2(5)$= 663.54 $Pr. > \chi^2$= 0.000	Wald $\chi^2(5)$= 686.92 $Pr. > \chi^2$= 0.000
α	5.47939**	4.42432**	4.03644**
	(0.46267)	(0.88682)	(0.90697)
$Year$	-0.10998**	-0.11485**	-0.11392**
	(0.02788)	(0.01780)	(0.01765)
$ln\ Employment$	0.53068**	0.31496**	0.27448**
$(units)$	(0.07412)	(0.12427)	(0.11896)
$ln\ Terminal\ area$	0.18970**	0.30548**	0.40622**
$(squaremeters)$	(0.08406)	(0.15199)	(0.17212)
$ln\ HHI$	0.44611**	0.78234**	0.79082**
	(0.04748)	(0.03736)	(0.03710)
$Interport$	-0.39488**	-0.72005**	-0.76576**
$(yes = 1 \quad no = 0)$	(0.11088)	(0.22074)	(0.22457)
η	-	-	-
Inefficiency model $Year$			
λ	8.38399	4.11368	2.61914
γ	0.98597*	0.94420*	0.87277*
σ_u^2	6.54807	1.59100	0.63539
σ_v^2	0.09316	0.09402	0.09262

** indicates the significance at least 5%; standard errors in parentheses. All regressions estimated with the sfcross and sfpanel routines in STATA 12 developed by Belotti et al. (2013). Note that * indicates the significance at 5% for Generalized Likelihood ratio-test of hypothesis (critical value are obtained from table of Kodde and Palm, 1986).

Log transformation of input and output variables allow us to compare coefficients and levels of significance across models. As expected, the coefficients have the positive sign with reference to employment and terminal area, due to the same directions of labour and infrastructural factors involving the total terminal's capacity and, therefore, increasing together with the rail tracks length. This also occurs because technological change is decreasing in the over period due to the high average overcapacity in many terminals as confirmed by the negative coefficient of the time trend ($Year$). Adding more quantities of production factors, such as labour and physical capacity, the rail productivity ratio RRI tends to increase.

On the contrary, the effect of the market power index is positive, and the localisation effect inside an interport (freight village) is negative due to the sign of the dummy variable *Interport* wich capture if this type of infrastructure allows to have greater output. At the same levels of traffic these results seem to favour infrastructures with less unutilized capacity regardless the contexts in which multi services business agglomeration forces are active (freight village).

The production frontier models suggest the existence of negative technical change over time as the negative signs of the significant parameters of the $Year$ variable indicate in the all frontier models (Table 3 and 4). It is common to expect a technique improvement in any industry over time but in the intermodal infrastructures this can be expected to have been driven over medium-long time period by new handling techniques; however, the signs of the trend input variable in all the models are negative. There are several factors which may contribute to the negative trend, of which the most important of these is overcapacity. Many Italian rail-road terminals have invested in high capacity

Table 4: Stochastic frontier estimation results Time-varying models

Production Frontier	B&C (92) Time-varying	B&C (95) Time-varying
Wald Test	Wald $\chi^2(5)$=	Wald $\chi^2(5)$=
	489.24	261.14
	$Pr. > \chi^2$=	$Pr. > \chi^2$=
	0.000	0.000
α	3.90275**	5.67643**
	(0.93127)	(0.49337)
Year	-0.08150**	-0.09654**
	(0.03329)	(0.03826)
ln Employment	0.26562**	0.53136**
(units)	(0.12132)	(0.07464)
ln Terminal area	0.40455**	0.18037**
(squaremeters)	(0.17024)	(0.08536)
ln HHI	0.78644**	0.49623**
	(0.03834)	(0.04249)
Interport	-0.80029**	-0.38774**
$(yes = 1 \quad no = 0)$	(0.22201)	(0.11141)
η	-0.02778NS	-
	(0.02417)	
Inefficiency model		
Year		0.08680NS
		(0.09827)
λ	2.78097	4.46019
γ	0.88550*	0.95214*
σ_u^2	0.70953	0.93287
σ_v^2	0.09174	0.04689

** indicates the significance at least 5%; standard errors in parentheses. All regressions estimated with the sfcross and sfpanel routines in STATA 12 developed by Belotti et al. (2013). Note that * indicates the significance at 5% for Generalized Likelihood ratio-test of hypothesis (critical value are obtained from table of Kodde and Palm, 1986). NS indicates "not significant".

infrastructures and facilities so the utilisation rate has dropped in the period and the production time trend is negative since the time variable ($Year$) is included in both the stochastic frontier and the inefficiency effect model. Considering the time varying models B&C(92) and B&C (95) the efficiency time trend is not significant. As a result, it does not allow an in-depth analysis of the efficiency dynamic in the period. The quasi-fixed nature of inputs related to the given installed capacity and the significantly high decrease in traffic in the years 2009-2010 might have determined for many terminals, a situation of overcapacity with a lower technical efficiency and its decay over time.

The results of all models show low average efficiency and a great potential for efficiency improvements of about 50 % among terminals even though the rail cargo market in Italy has declined in recent years. Therefore, the topic of the next section is to test the correct models hypotheses that indicate changes in the technical efficiency over time (time varying).

4.1 Time-varying Technical Efficiency

Figure 1 shows the Kernel density distribution of the technical efficiency estimates for the models Stevenson (80), B&C (92) and B&C (95), and Figure 2 shows the first quartile, mean and third quartile scores per years for the same models. In particular, in Figure 1, the three kernel density estimators for B&C (95), B&C (92) and Stevenson (80) show completely different assessment, both in the pattern and the magnitudes in the estimated values. Moreover, the technical efficiency for the model B&C (92) is decreasing, while the model B&C(95) and Stevenson (80) show the same trend (see Figure 2). In addition, the spread of efficiency scores (inter-quartile range) is wider in B&C (92).

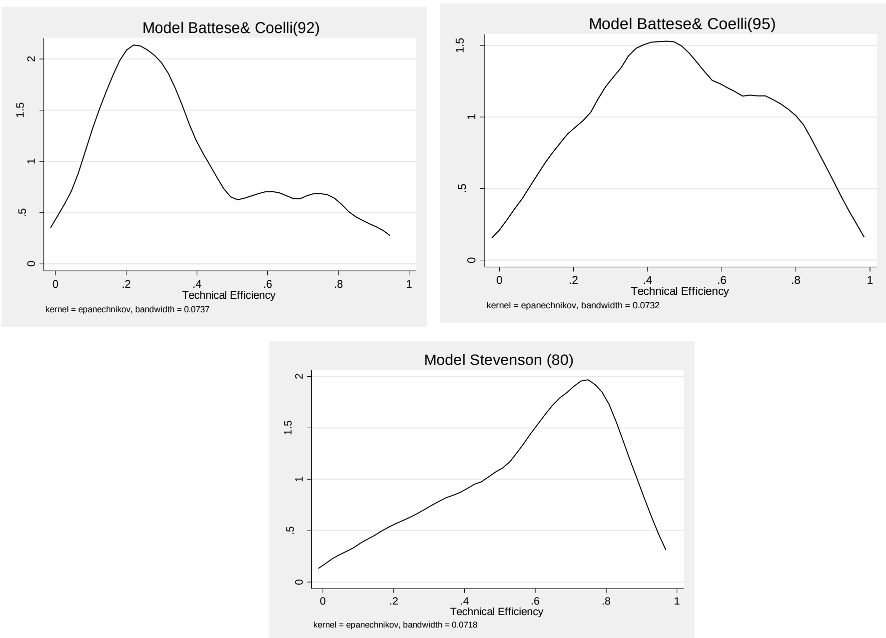

Figure 1: Technical efficiency distribution of sample rail-road terminals for B&C (92), B&C (95) and Stevenson (80) models

Finally, the Andrew's curves (Andrews, 1972) in Figure 3 show that for the model B&C(92) all rail-road terminals preserve the same pattern but the level of technical efficiency is different. We can note a bundle of functions, compact and neighboring (in term of distance in the space of more dimension), that leads to the formation of the clusters. In B&C (95) and Stevenson (80) the last rail-road terminals represent unusual

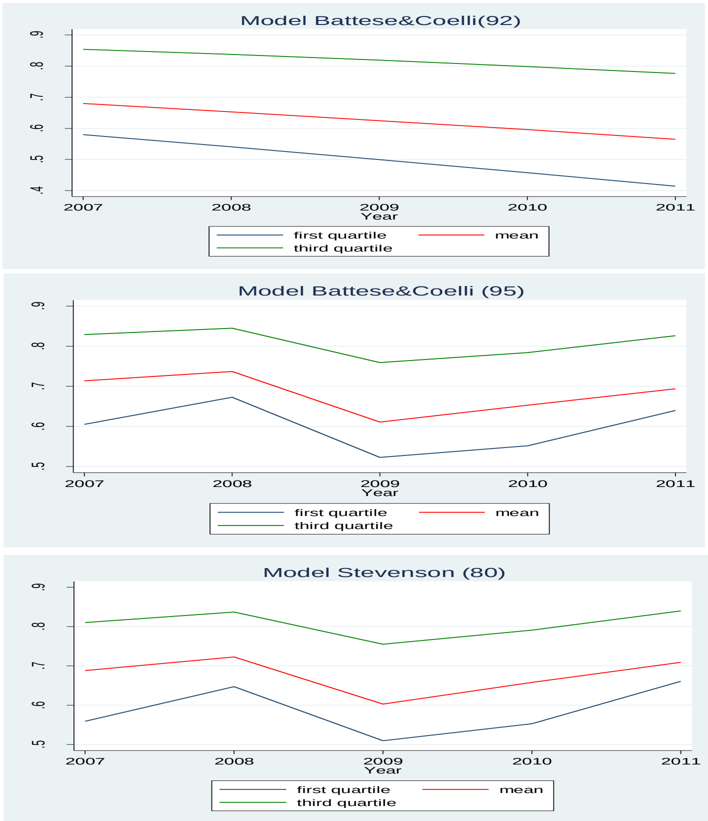

Figure 2: The first quartile, mean and third quartile values of technical efficiency of sample rail-road terminals for B&C (92), B&C (95) and Stevenson (80) models

observation that does not follow the pattern of the others. In particular, for rail-road terminal Marcianise and Lugo we can note that, for a given value of t, $(t \sim 1)$ to a shift of $f_x(t)$ to the right, attributable both to the lower value of technical efficiency and to the lower production levels in more years, and then, a low market power with a low level of competition. In particular, these terminals are the last in the average time varying efficiency rankings where the infrastructural overcapacity reaches the maximum level considering the capacity utilization ratio which is low due to the lack of intermodal rail-road traffic.

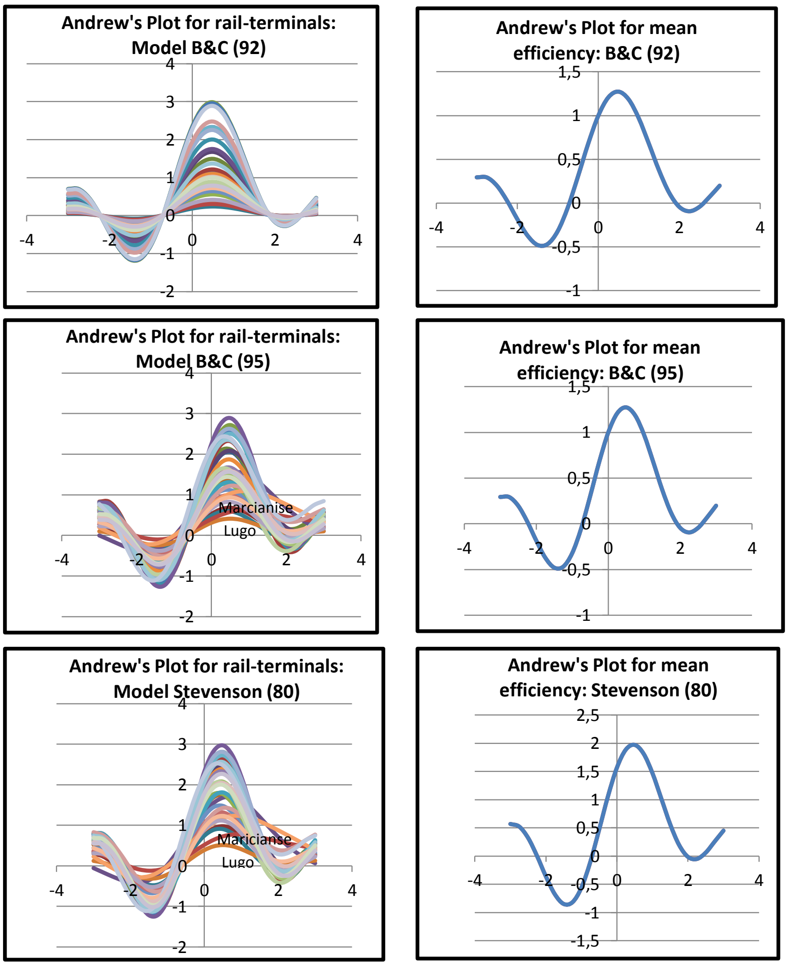

Figure 3: Andrew's plot for rail-road terminals efficiency: B&C (92), B&C (95) and Stevenson (80) models

On the ground of these results, both B&C (95) and Stevenson (80) have been revised considering the effects on inefficiency related to the different levels of intermodal traffic expressed by the variable $Total\ intermodal\ traffic$ (Table 5). In particular, due to presence of small rail terminals with high efficiency and large terminals with low efficiency, we have tested if the efficiency can be related to the volume of total intermodal traffic as a dimensional aspect of the terminals. This problem could be also linked to the presence of heteroskedasticy in the error component. The heteroskedasticy test confirms the presence of variations in variance in idiosyncratic error component despite the output and the input variables have been normalized with respect to the rail tracks length. Heteroscedasticity can occur due to differences in the size of firms included in a dataset. Not accounting for heteroscedasticity might lead to biased parameter and efficiency estimates (Hadri et al., 2003). We, therefore, let the standard deviation of the two-sided noise term v_{it} vary with the variable *Rail tracks length* of terminals as a proxy variable for their size. For this reason, we have specified in the B&C(95) and Stevenson (80) models that the idiosyncratic error component is heteroskedastic.

To overcome this drawback we have considered in the B&C (95) time varying inefficiency effects model, and in the Stevenson (80) pooled model the total intermodal traffic to estimate both the frontier and the inefficiency effects in one stage. The time variable is included in both the stochastic frontier and the inefficiency effect model. Within the stochastic frontier it accounts for technological change while, within the inefficiency effect model, it accounts for changes in technical efficiency. This one-stage approach provides more reliable predictors of firm-specific efficiency than using a two-stage approach, which performs a second-stage regression of the first-stage efficiency scores upon certain environmental or other firm-specific factors. In the inefficiency part of the model a negative sign represents a negative effect on inefficiency and, thus, a positive effect on efficiency. Table 5 shows that the results of the inefficiency models confirm a positive effect of the total traffic volume on efficiency and a small but negative technical efficiency variations over time.

Table 5: Stochastic frontier estimation results Stevenson (80) and B&C(95)

Production Frontier	Stevenson (80) Pooled	B&C(95) Time-varying
$Wald\ Test$	Wald $\chi^2(5)$=143.96	Wald $\chi^2(5)$=143.93
	$Pr. > \chi^2 = 0.000$	$Pr. > \chi^2 = 0.000$
α	5.423167**	5.425381**
	(0.466245)	(0.465678)
$Year$	-0.08559**	-0.08565**
	(0.025282)	(0.025239)
$ln\ Employment\ (units)$	0.512444**	0.511841**
	(0.076411)	(0.07634)
$ln\ Terminal\ area\ (squaremeters)$	0.188582**	0.187272**
	(0.086346)	(0.086091)
$ln\ HHI$	0.323048**	0.322862**
	(0.042384)	(0.042396)
$Interport$	-0.39231**	-0.39181**
$(yes = 1 no = 0)$	(0.103028)	(0.102954)
Inefficiency model		
$Total\ intermodal\ traffic$	-0.37642**	-0.37753**
	(0.071676)	(0.072129)
$Year$	0.001834**	0.001836**
	(0.00025)	(0.000251)
$Usigma$		
$Constant$	-0.25868NS	-0.24994NS
	(0.334024)	(0.334487)
$Vsigma$		
$Rail\ tracks\ lenght$	-0.37439**	-0.37581**
	(0.057656)	(0.057553)
λ	3.62738	3.66263
γ	0.92937	0.93063
σ_u^2	0.05868	0.05806
σ_v^2	0.77207	0.77884

** indicates the significance at least 5%; standard errors in parentheses. All regressions estimated with the sfcross and sfpanel routines in STATA 12 developed by Belotti *et al.*Belotti et al. (2013). NS indicates "not significant".

Moreover, we have divided the terminals into three classes concerning the total intermodal rail traffic and carried out the Kruskal-Wallis Rank test in order to verify the equality of the medians of the three groups. We have obtained a p-value <0,05 which leads us to a accept the hypothesis that these groups come from by populations with different medians and that the dimensional aspect relative the throughput is relevant to model the technical efficiency. Now, from the Kernel density estimators for B&C (95) and Stevenson (80) models, we make the same assessment, both in the pattern and the magnitudes in the estimated values. The technical efficiency index in Table 6 for the two time varying models reveals that the average efficiency scores for the whole period is very similar. The ranking highlights the significant degree of efficiency over 0.7 of the rail terminals of Northern Italy, particularly specialized in cross-frontier rail traffic in the Alps, especially with Central Europe (Germany, Austria, Switzerland and France). The Milan Certosa, Padua, Verona, Parma and Gallarate terminals, set alongside the main lines of trans-European traffic which cross the Po Valley, perform a role of the first order within the total balance of goods traffic passing between Northern Italy and the rest of Europe. Milan Certosa, Gallarate, Milan Smistamento, and Rho intermodal terminals, located in the region of Lombardy, not inside an interport (freight village), achieve a very good level of efficiency. Leghorn and Bari Ferruccio intermodal terminals have the highest efficiency among those closer to the ports. Many terminals lie below the average efficiency and, in particular, those belonging to Central-Southern Italy.

Table 6: Average time varying efficiency scores

Terminal	Stevenson (80)	Terminal	Battese and Coelli (95)
Milan Certosa	0.8769	Milan Certosa	0.8774
Padua	0.8001	Padua	0.8003
Verona	0.7972	Verona	0.7972
Parma/Castelguelfo	0.7952	Parma/Castelguelfo	0.7958
Gallarate	0.7604	Gallarate	0.7607
Leghorn Guasticce	0.7536	Leghorn Guasticce	0.7543
Padua Scalo	0.7204	Padua Scalo	0.7207
Maddaloni Marcianise	0.7203	Maddaloni Marcianise	0.7201
Milan Smistamento	0.7088	Milan Smistamento	0.7087
Bari Ferruccio	0.7073	Bari Ferruccio	0.7074
Brescia	0.6888	Brescia	0.6885
Gela	0.6872	Gela	0.6880
Novara	0.6744	Novara	0.6744
Rome Smistamento	0.6486	Rome Smistamento	0.6489
Brindisi	0.6344	Brindisi	0.6343
Rho	0.6155	Rho	0.6159
Trento	0.6124	Trento	0.6118
Melzo	0.5633	Melzo	0.5631
Piacenza	0.5540	Piacenza	0.5530
Catania Bicocca	0.5512	Catania Bicocca	0.5504
Milan Segrate	0.5437	Milan Segrate	0.5429
Torino Orbassano	0.5186	Torino Orbassano	0.5180
Candiolo	0.3907	Candiolo	0.3900
Mortara	0.3547	Lamezia Terme	0.3550
Lamezia Terme	0.3546	Mortara	0.3538
Busto Arsizio	0.3333	Busto Arsizio	0.3327
Rivalta Scrivia	0.3237	Rivalta Scrivia	0.3235
Nola	0.3152	Nola	0.3146
Pescara Porta Nuova	0.3078	Pescara Porta Nuova	0.3077
Bologna	0.2988	Bologna	0.2978
Pomezia-S. Palomba	0.2963	Pomezia-S. Palomba	0.2959
Palermo Brancaccio	0.2626	Palermo Brancaccio	0.2623
Marcianise	0.1832	Marcianise	0.1828
Lugo	0.1215	Lugo	0.1211
Mean efficiency	0.5434	Mean efficiency	0.5432

5 Discussion

This study focuses on productivity and efficiency of 34 Italian intermodal rail terminals observed over the period 2007-2011. Different stochastic frontier models have been estimated assuming a production function where the annual rail road index (RRI) of the terminals is assumed to be obtained by combining four factors: labour, terminal area, market power and the localization in a logistics centre. Particular attention was paid to analysis of technological change in production output and technical efficiency levels over time, applying the most useful and suitable econometric models existing in literature. Panel data frontier model estimation has been widely used to estimate technical efficiency in passengers and freights railways sector (Wetzel et al., 2008; Smith and Christopher, 2014). We tried to demonstrate the range of available models and study differences between them in the assessment of changes in rail terminals efficiency performance over time, as well as technological change over the period of the study. The variability of the results from different models clearly demonstrates the difficulty in choosing a model. No model can be held to be correct' and the efficiencies will always be a kind of unobserved or modeled effect. A model choice in empirical research should not be based on standard practice', but on a reasoned choice. In this study we have observed a probable problem of heterogeneity and heteroscedasticity due to the different size and capacity of the analyzed intermodal infrastructures. In the transport infrastructural context large technical endowment may create a negative impact on efficiency. A primary factor characterizing railway networks is network density (network length in km per square area km). The impact of network density on efficiency is not necessarily clear. A higher network density could increase coordination and maintenance costs of the network, leading to a negative impact on efficiency (Wetzel et al., 2008). Therefore, concerning port efficiency and effectiveness estimate with the SFA, empirical studies found that the bigger the number of terminals, docks, shipyards, etc., the bigger the probability of a lower efficiency score (Pagano et al., 2013). The results achieved by the application of stochastic frontier models confirm the medium-high rates of inefficiency which characterize many Italian rail-road terminals due to the overcapacity phenomenon; the average level of efficiency dramatically differs among the various Italian regions and it is higher considering the trade lanes of cross-border traffic, in particular Germany-Italy and Belgium-Italy. The different assumptions about the different throughputs among the terminals and the technical capacity heterogeneity improve the results that also highlight the similarity between the time varying B&C (95) model and the pooled SFA Stevenson (80) model. Most of the rail terminals that are large in production scale are more likely to be associated with higher production quantitative scores but not always with higher efficiency scores. This is an effect of the overcapacity confirmed by the low-medium efficiency level. All applied models show a negative technological change over the period 2007-2011, as well as a little negative technical efficiency growth considering also the severe fall in demand in the years 2009 and 2010. The slightly negative pattern of efficiency over the sample period might be due to unclear evidence of the crisis in terms of supply reaction and to the high structural capacity in relation to the effective level of demand. The growing proportion of spare capacity is reflected by the negative change in the technical efficiency.

Acknowledgement

We would like to thanks the anonymous referees for carefully reading our manuscript and for giving such constructive comments which substantially helped improving the quality of the paper.

References

Ahn, S. C., Lee, Y. H., and Schmidt, P. (2001). Gmm estimation of linear panel data models with time-varying individual effects. *Journal of Econometrics*, 101(2):219–255.

Aigner, D., Lovell, C. K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1):21–37.

Andrews, D. F. (1972). Plots of high-dimensional data. *Biometrics*, pages 125–136.

Ballis, A. and Golias, J. (2002). Comparative evaluation of existing and innovative rail–road freight transport terminals. *Transportation Research Part A: Policy and Practice*, 36(7):593–611.

Baltagi, B. H. (1985). Pooling cross-sections with unequal time-series lengths. *Economics Letters*, 18(2):133–136.

Battese, G. E. and Coelli, T. (1991). *Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India*. Department of Econometrics, University of New England Australia.

Battese, G. E. and Coelli, T. J. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics*, 38(3):387–399.

Battese, G. E. and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20(2):325–332.

Battese, G. E., Coelli, T. J., Colby, T., et al. (1989). *Estimation of frontier production functions and the efficiencies of Indian farms using panel data from ICRISAT's village level studies*. Department of Econometrics, University of New England.

Belotti, F., Daidone, S., Ilardi, G., and Atella, V. (2013). Stochastic frontier analysis using stata. *Stata Journal*, 13(4):719–758.

Bonara, G. and Focacci, C. (2002). Progettazione e funzionalitá degli impianti ferroviari. *CIFI*.

Boysen, N., Fliedner, M., Jaehn, F., and Pesch, E. (2012). Shunting yard operations: Theoretical aspects and applications. *European Journal of Operational Research*, 220(1):1–14.

Cheon, S., Dowall, D. E., and Song, D.-W. (2010). Evaluating impacts of institutional reforms on port efficiency changes: Ownership, corporate structure, and total factor productivity changes of world container ports. *Transportation Research part E: Logistics and Transportation Review*, 46(4):546–561.

Cornwell, C., Schmidt, P., and Sickles, R. C. (1990). Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics*, 46(1):185–200.

Cullinane, K., Song, D.-W., Ji, P., and Wang, T.-F. (2004). An application of dea windows analysis to container port production efficiency. *Review of Network Economics*, 3(2).

Greene, W. (2005a). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis*, 23(1):7–32.

Greene, W. (2005b). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, 126(2):269–303.

Greene, W. H. (1980a). Maximum likelihood estimation of econometric frontier functions. *Journal of Econometrics*, 13(1):27–56.

Greene, W. H. (1980b). On the estimation of a flexible frontier production model. *Journal of Econometrics*, 13(1):101–115.

Hadri, K., Guermat, C., Whittaker, J., et al. (2003). Estimating farm efficiency in the presence of double heteroscedasticity using panel data. *Journal of Applied economics*, 6(2):255–268.

Henderson, D., Simar, L., et al. (2005). A fully nonparametric stochastic frontier model for panel data. Technical report, State University of New York at Binghamton.

Higgins, C., Ferguson, M., and Kanaroglou, P. (2012). Varieties of logistics centers: Developing standardized typology and hierarchy. *Transportation Research Record: Journal of the Transportation Research Board*, (2288):9–18.

Janic, M. (2007). Modelling the full costs of an intermodal and road freight transport network. *Transportation Research Part D: Transport and Environment*, 12(1):33–44.

Jaržemskiene, I. (2009). Research into the methods of analysing the productivity indicators of transport terminals. *Transport*, 24(3):192–199.

Jondrow, J., Lovell, C. K., Materov, I. S., and Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19(2-3):233–238.

Kodde, D. A. and Palm, F. C. (1986). Wald criteria for jointly testing equality and inequality restrictions. *Econometrica: Journal of the Econometric Society*, pages 1243–1248.

Kumbhakar, S. C. (1990). Production frontiers, panel data, and time-varying technical inefficiency. *Journal of Econometrics*, 46(1):201–211.

Kumbhakar, S. C., Ghosh, S., and McGuckin, J. T. (1991). A generalized production frontier approach for estimating determinants of inefficiency in us dairy farms. *Journal of Business & Economic Statistics*, 9(3):279–286.

Lee, Y. H. and Schmidt, P. (1993). A production frontier model with flexible temporal variation in technical efficiency. *The Measurement of Productive Efficiency: Tech-*

niques and Applications, pages 237–255.

Medda, F. and Liu, Q. (2013). Determinants and strategies for the development of container terminals. *Journal of Productivity Analysis*, 40(1):83–98.

Meeusen, W. and Van den Broeck, J. (1977). Efficiency estimation from cobb-douglas production functions with composed error. *International Economic Review*, pages 435–444.

Pagano, A. M., Wang, G. W., Sánchez, O. V., and Ungo, R. (2013). Impact of privatization on port efficiency and effectiveness: results from panama and us ports. *Maritime Policy & Management*, 40(2):100–115.

Pels, E., Nijkamp, P., and Rietveld, P. (2003). Inefficiencies and scale economies of european airport operations. *Transportation Research Part E: Logistics and Transportation Review*, 39(5):341–361.

Pitt, M. M. and Lee, L.-F. (1981). The measurement and sources of technical inefficiency in the indonesian weaving industry. *Journal of Development Economics*, 9(1):43–64.

Reifschneider, D. and Stevenson, R. (1991). Systematic departures from the frontier: a framework for the analysis of firm inefficiency. *International Economic Review*, pages 715–723.

Schmidt, P. and Sickles, R. C. (1984). Production frontiers and panel data. *Journal of Business & Economic Statistics*, 2(4):367–374.

Smith, A. S. and Christopher, N. (2014). Rail efficiency: cost research and its implications for policy.

Stevenson, R. E. (1980). Likelihood functions for generalized stochastic frontier estimation. *Journal of Econometrics*, 13(1):57–66.

Tongzon, J. and Heng, W. (2005). Port privatization, efficiency and competitiveness: Some empirical evidence from container ports (terminals). *Transportation Research Part A: Policy and Practice*, 39(5):405–424.

Wetzel, H. et al. (2008). *European railway deregulation: the influence of regulatory and environmental conditions on efficiency*. Inst. für Volkswirtschaftslehre.

Yan, J., Sun, X., and Liu, J. J. (2009). Assessing container operator efficiency with heterogeneous and time-varying production frontiers. *Transportation Research Part B: Methodological*, 43(1):172–185.